# Identification and Classification of Industrial Plastic Waste Using Deep Learning Models

MSc Research Project
MSc in Data Analytics


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# Identification and Classification of Industrial Plastic Waste Using Deep Learning Models

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**Abstract**

Waste management is a critical issue that all major urbanized communities must address. In today's world, sustainable growth is targeted by major economies, and waste management is one of the areas that will help with that. Abundant research has been conducted into automating waste separation to segregate the waste from recyclable to non-recyclable. The margin for human error is reduced by the introduction of automation. Machine learning and advanced deep learning models, assist in reaching this goal by allowing for the construction of high-accuracy models. The segregation of plastic trash into plastic types was the emphasis of this study paper. The current research proposes the development of an automated system that uses deep learning models to classify plastic garbage. This study aims to develop a model that is highly accurate, scalable, and simple. The study experimented with three models, Inception-ResNet-v2, VGG19, and Xception. VGG19 delivered promising results and is better than the state-of-the-art canny edge detection-based model by almost 22%.

***Plastic Waste Management, Deep Learning, Transfer learning, VGG19, Xception, Inception***

# 1 Introduction

Waste management is critical in today's society, where there is a strong focus on sustainable growth while also protecting the environment. By effectively controlling trash, the research project will contribute to long-term growth. This section will provide the context for the proposal, the rationale for the research, major findings from similar studies, and general conclusions from the review.

## 1.1 Background

Waste management is a major issue in all urbanized cities with residential and business settlements, and it is a part of everyone's daily existence. Along with trash management, everyone must ensure that waste is recycled and segregated as suggested by Singh et al. (2014). This will result in lower pollutants, energy savings, and long-term sustainability as advocated by Zaman (2016). Multiple models have been developed to classify the recyclable waste and non-recyclable waste utilizing deep learning algorithms combined with mechanical setup. The system developed has automated the garbage classification process and has demonstrated encouraging results as shown in Seadon (2010). This research will evaluate deep learning models to compare their results for the classification of the plastic waste. The deep learning models that are effective for image classification like CNN and Inception will be studied in this research. Image classification models developed using these models have promising results and are easily replicable.

## 1.2 Motivation

Environmental protection is a priority for all major countries in long-term planning; it is a pressing need. As a result, every individual as a global citizen has a responsibility to contribute to this cause. Plastic waste is the topic of the proposed research. Plastic waste is generated at a rate that is faster than ever before. Micro-plastics have found their way into the food chain as a result of plastic waste's deep penetration of the ecosystem as explained by Ritchie and Roser (2018). If this problem is not addressed, it will cause irreversible damage in the future. To avoid a situation like this, we must take proactive steps to reduce the impact of plastic trash. By identifying and recycling plastic garbage, it is vital to find strategies to reduce the amount of plastic waste disposed as proposed in Horejs (2020). However, some of the plastics currently in use are not fully recyclable and must be manually sorted. To reduce waste, an effective approach for identifying and classifying recyclable plastic is required. This will aid in the development of an automated system that not only detects but also separates garbage. A system that is constantly learning depending on changing needs and is unsupervised can be constructed using advanced machine learning models as shown in Hussain et al. (2020).

## 1.3 Research Question

The following is the proposed research question: "How can deep learning models for industrial trash be utilized to properly identify and classify plastic garbage for better waste management?" Artificial neural networks are employed by deep learning models to extract data through representation learning. Waste management refers to the process of managing waste from its inception to its disposal.

## 1.4 Academic Justification

The assessment of academic literature based on waste management activity has provided us with a wealth of information. From smart waste collection to waste classification, machine learning and its deep learning capabilities have aided several research projects in the area of waste management. The field of plastic waste segregation is underdeveloped and has a lot of room for improvement. Deep learning models paired with IoT can help boost this research area. They can be further integrated with many more applications which can range from households to large-scale industrial setups.

## 1.5 Objectives and Deliverables

The research aims to bring forth the outcomes of deep learning application on plastic waste sorting that can further help in their efficient disposal. The overview and background of the research have been covered in Section 1.

The past work that has been referred and which have helped in the research have been discussed in Section 2 and Section 3 briefly discusses the methods chosen for the research and the Section 5 provides the implementation details and Section 7 concludes the work and puts light on the future work that can be carried out in the field. The research objectives have been listed below:

- Implementing models for plastic image classification
- Comparing and analyzing the models

The timeline for the project has been laid down as shown in Figure 1.

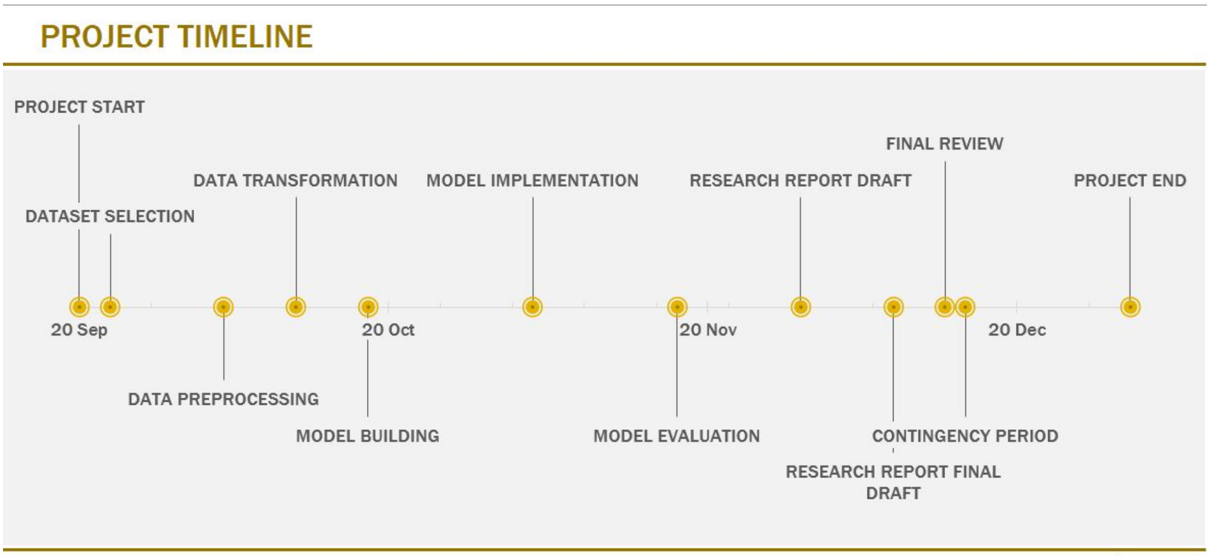


Figure 1: Project Timeline

# 2 Related Work

Garbage management systems must be implemented to classify waste efficiently and sustainably, as well as to reduce disposable waste as shown in Loussaief and Abdelkrim (2016). The current waste management plan followed globally focuses on disposal of waste rather than recycling. Waste management is always associated as the government's responsibility, but it is now the responsibility of businesses and individuals as proposed in Zaman (2016). This is demonstrated by the fact that only 15% of municipal waste collected is recycled, even though it accounts for 84 per cent of the total waste collected. Unrecycled garbage ends up in landfills and dumping sites, which are problematic since they result in waste spills into the air and water due to burning and other activities. Many industrial wastes, in particular, must be dealt with because they are the major contributors to non-biodegradable and dangerous pollutants. Plastics are the major contributors to non-degradable waste, and recycling them is more favourable than disposing as demonstrated by Lazarevic et al. (2010). Recycling using mechanical means is the widely used method for dealing with plastic, but the category of plastic has an impact on the recycling benefits. Some plastics are effectively recycled, while others do not provide significant benefits since the residue formed during recycling has an environmental impact. The discussed factors motivate this research to build a plastic classification model.

## 2.1 Object Identification Using Machine Learning

There are many demonstrated application of machine learning for image identification and classification. When a decent training dataset is provided, the results and accuracy obtained from various machine learning models are excellent as shown in Saha et al. (2018). This study was successful in illustrating how machine learning may aid in the automation of the item labelling process, removing any human error possibilities. The models were tested on three different datasets. The results revealed that the ANN (Artificial Neural Networks) model was stable across datasets and had around 100% accuracy. Machine learning techniques are an excellent way to automate item categorization and labeling activities, according to the overall conclusion reached.. Measurable error is present when manual classification and sorting mechanisms are applied.

Feature extraction and image classification approach for pollen photographs were investigated in Popescu and Sasu (2014). Because the dataset employed for pollen identification was tiny, subpar investigation results were delivered. Deep learning models were not used in the research. To evaluate the outcomes in image classification, it will be advantageous to employ a big image set and apply deep learning models.

The Support Vector Machine(SVM) classifier model is more advanced and complex compared to standard machine learning models as studies shown in Tzotsos and Argialas (2008). When the photos are segmented and then used in an SVM model, they produce good results. For object-based image analysis, this approach is particularly effective. This paves the path for SVM to be utilized with rule-based classifiers in the future.

## 2.2 Deep Learning Models for Object Detection

Using a collection of efficient modelling components, image classification using deep learning models may be efficiently done, allowing for the establishment of a baseline performance as stated by Chan et al. (2015). Using components such as cascaded PCA, binary hashing, and block histograms, the unsupervised deep learning image classification PCANet is straightforward to construct. PCANet has been found to outperform its extensions, such as RandNet and LDANet, in facial recognition. PCANet is the foundation for understanding the most complex deep learning categorization models.

Deep learning models can be implemented in a variety of ways, including convolutional neural networks (CNN), as shown in Al-Saffar et al. (2017). Traditional CNN models are good at picture classification, but they can't handle spatial invariance in images. The CNN model now can handle spatial invariance in images thanks to the newly incorporated spatial transformer. It is fascinating to see how well the CNN model does with a dataset with a lot of image invariance. Overall, the CNN model's picture handling capabilities have greatly improved.

Many deep learning models have gained popularity in recent years and are being used to analyze real-world scenarios. Tang et al. (2017), compares a few models based on regression and region suggestions. SSD (single shot multi-box detector) has superior accuracy than YOLO (You Only Look Once), which is a end-to-end deep learning model, among the regression models. R-FCN and faster R-CNN have the same level of accuracy, however, R-FCN is quicker than faster R-CNN in terms of speed. The comparative study aids in comprehending the accuracy provided by various models as well as the obstacles that each model faces.

Hybrid inception models have showed promising results for image recognition. The hybrid inception models have added residual connections in the newtork that lead to drastic improvement in the image recognition capability. Inception-ResNet-v2 is one of the hybrid models with improved image recognition capabilities as analyzed in Szegedy et al. (2017). The Xception model which is extreme version of inception model has shown excellent results in pneumonia detection using chest X-ray samples as shown in Ayan and Ünver (2019).

## 2.3 Deep Learning Models for Waste Classification

In this work, Adedeji and Wang (2019), the classification of waste from urban garbage collection was done using deep learning models and CNN. The model utilized was ResNet-50, a pre-trained 50 layer model. After feature extraction, the data was modelled using a multiclass SVM. Given the short collection of 1989 photos, the accuracy attained from the dataset was 87 per cent, which is excellent. This goes on to illustrate that by using appropriate modelling techniques, better accuracy may be achieved on the dataset.

Another noteworthy waste categorization study uses multilayer perceptrons (MLP) to combine visual information from manually labelled rubbish photographs Chu et al. (2018). The study was carried out with the help of a multilayer hybrid deep learning system (MHS), which had a 90% accuracy rate. The model then outperforms the R-CNN model, which exclusively uses picture inputs. This throws a lot of light on MHS's superiority to traditional systems in terms of reliability.

The TrashNet collection, which contains 2527 photos, was used to classify waste using image recognition in this work Mao et al. (2021). DenseNet121 was created by utilizing a genetic approach to fully use DenseNet 121's connected layers. The enhanced DenseNet121 had a precision of above 99 per cent, according to the study. Gradient weighted class activation enhanced the model's explainability by emphasizing the coarse characteristics of the images used.

This research Vo et al. (2019) created a deep neural network for garbage separation called DNN-TC. The ResNet model has been improved by the DNN-TC model. This model aims to deliver improved predictive performance for the TrashNet and VN-trash datasets, with an accuracy of 94 to 98 percent. Most state-of-the-art models perform worse than the model that was produced.

This research Ekundayo et al. (2021) created a waste classification system to classify waste and categorize them into recyclable and non-recyclable waste. This work demonstrated the different deep learning models and their capabilities as a system to classify waste. From this research, it was seen that Inception-Resnet-V2, MobileNetV2, and DenseNet201 have good results when it comes to image classification.

## 2.4 Common Challenges Faced in Deep Learning Models

The photo classification scenario is one of the most common applications of deep learning. The challenge faced by most image classification problems is the lack of sufficient training data as shown in Mikołajczyk and Grochowski (2018). To overcome this issue, data altering methods like rescaling, flipping and so on need to be applied on the dataset to build a sizable dataset for training, which aids in training the models for better performance. Three case studies of medical data for medical diagnosis were used to assess this strategy for data deficiency.

In many circumstances, where a large dataset of photos may be gathered, it is not practical, and a different method to dataset modelling is required Wang et al. (2020). A medical CT scan image collection for liver lesions was initially utilized to build a deep learning model with CNN, however the performance was poor.The image set used was not large, hence the accuracy was limited. Collecting large liver CT scan images is not practical. The training photo collection proceeded through three steps before the model was trained to improve accuracy. The three steps are non-contrast (NC), arterial (ART), and portal venous (PV). The accuracy obtained by combining the three phases was much higher, reaching about 91 per cent accuracy. A similar approach can be used to improve performance for deep learning models using a limited training dataset.

The end-to-end deep learning model Yolo, has gained popularity in recent years due to its strong object detection and classification capability. In this study Shetty (2020), deep sea debris of waste was identified and classified using Yolov3. The model was efficient to identify and classify the images. The newer version of Yolov4 is also effective in image classification. It outperforms the state-of-the-art canny edge filter models by 21% as shown in Padalkar (2021).

## 2.5 Conclusion

As seen in the review of previous works done in the field of image classification, deep learning models have shown promising results and are highly efficient in classification problems. We have concluded to use Inception-Resnet-v2, VGG19, and Xception models to classify the plastic waste dataset.

# 3 Research Methodology

The processes followed under the design specification and implementation sections will be briefly covered in this section below, which will quickly address the details connected to the specific methodology employed for this research project. The analysis is carried out to explain why some models, approaches, and processes are chosen over others, using supporting papers and stated explanations concerning current works in this research area. To begin this research, two key research approaches, KDD and CRISP-DM, were explored. This approach helps in attaining better results as shown in Fayyad et al. (1996). Figure 2 depicts the many steps of the research technique in a graphical depiction.

## 3.1 Understanding the Project and Application Domain

The initial stage in conducting the study was to comprehend the research question, research area, existing work done in the field. Delivering a holistic solution required a clear understanding of the waste management systems in use. Waste management has been more inclined towards the segregation of waste matter based on the materials like wood, plastic, glass and so on. There is less work done to build an efficient plastic waste dataset and models that can efficiently identify the type of plastic. The various resources that can provide overall plastic waste datasets have been explored. The initial model building phase was based on simple models like CNN.

## 3.2 Understanding the Data

A careful analysis was done on the various databases and datasets available online to find a reliable plastic waste dataset. After looking at the options available, the WaDaBa

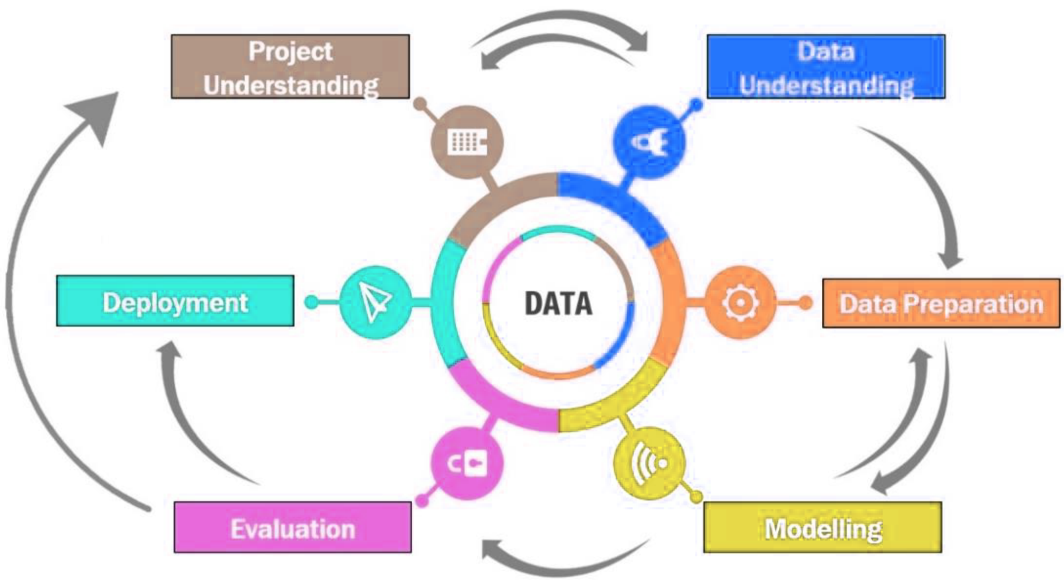


Figure 2: Research Methodology

plastic waste images database by J. Bobulski (2018) was finalized for the research from their website [1]. The database has plastic waste images of major plastic types such as PET, PEHD, PP, PS, OO. The dataset is enriched with a wide range of images from different lighting conditions and pictures taken from different angles. Data augmentations applied to this dataset will help build strong training models for testing.

## 3.3 Data PreProcessing and Transformation

Data Preparation is the most critical element in achieving successful outcomes. Preprocessing the data is vital before applying any models, and techniques including data embedding, image resizing, and normalization were employed to assure data consistency. Additionally, trials were performed to visualize the data using various Python libraries and alter the data as needed. Also, the Roboflow app [2] was used for the downsizing and modification of the dataset as per the model's requirement.

## 3.4 Data Modelling

The models picked for classification have been analyzed through careful analysis during literature review. The data has then been divided into train, test, and validation test as per the need of each model. The CNN-based models that have been used to categorize plastic images into various categories and match the study question's parameters are listed in the sections below.

[1] WaDaBa plastic database: `http://wadaba.pcz.pl/`
[2] Roboflow: `https://app.roboflow.com/login`

### 3.4.1 Inception-Resnet-v2

This function returns a Keras image classification model with pre-trained ImageNet weights if desired. It falls under the inception model family. It has residual connections that replace the final concatenation layer of the traditional inception model and has been demonstrated for classification in Ferreira et al. (2018).

### 3.4.2 VGG19

VGG19 is a type of CNN network which is a variant of VGG16. It is a 19 layered variant of the VGG architecture. It takes in images of 224 by 224 as a default. It offers more customization capabilities compared to the previous versions of the architecture as elaborated in Dey et al. (2021).

### 3.4.3 Xception

Xception is deep learning network comprised of 71 layers based on CNN. The network has strong image recognition capability as it can be trained with the ImageNet weights. This makes it capable of recognizing and classifying images from a large category group. As seen in Chollet (2017), the network's picture input size is 299 by 299 pixels.

## 3.5 Results and Evaluation

It is critical to have a thorough understanding of each model's efficiency after it has been implemented. The performance of the models can be measured using a variety of indicators. This will aid in the identification of the best-performing model and subsequently focus on that model to improve performance. The evaluation processes will assist in determining whether or not the research requirements are fulfilled. Our primary criterion for evaluating the models' performance will be test accuracy. Precision, recall, and the f1 score, among other metrics, will be examined in depth during the analysis and evaluation.

## 3.6 Research Deployment

The deployment and analysis of the models that have been implemented to provide informed insights is the final element in the research delivery and methodology. This step is given special attention to determine whether the research study conducted is meant to become a part of everyday life. Depending on the sort of system in which it is implemented, the detected activity varies.

# 4 Design Specification

The plastic waste classification modelling is done based on a two-tier architecture. The first tier is the business layer where all data preprocessing and modelling is carried out, the second tier is the presentation tier where the results and insights gained are visualized for analysis. Figure 3 shows the design specification architecture for the plastic waste sorting model.

When it comes to design work, this study pays special emphasis to the business layer. The building of this tier of the architecture is covered in full in Section 5, however the vital points are summarized in Table 1. To aid in the repeatability of the trials done,


Figure 3: Design Approach

the design implementation is open to fresh iterations and experimentation. This method aids in achieving the finest potential outcomes.

Table 1: Business Layer

| **Data Collection** | **PreProcessing** | **Modelling** | **Evaluation** |
|---|---|---|---|
| WaDaBa DataSet | Augmentation | ResNet Inception V2 | Test Accuracy |
| WaDaBa DataSet | Augmentation | VGG19 | Test Accuracy |
| WaDaBa DataSet | Augmentation | Xception | Test Accuracy |

The hardware and software requirements for the research work carried out has been documented in a separate document as a configuration manual. The configuration manual has been provided along with the research paper. This will help in understanding the testing conditions for the models.

# 5 Implementation and Solution Development

In this study, the classification models were implemented in such a way that the characteristics from the dataset could be extracted and used to improve the model's prediction capabilities. The models' goal is to correctly identify the plastic category with minimum errors; the challenges encountered are listed below:

- The WaDaBa dataset had to be downsized because the original dataset had big image files that slowed down processing.

- To derive a good prediction, the models in use must be pre-trained, and transfer learning with custom layers on the learned models must be conducted. The images of different categories sometimes hold great resemblance and need high accuracy.

## 5.1 Data Collection

The core of the research is building a versatile model that will give high accuracy and is easily replicable for real-life scenarios. The foundation for building a model relies on feeding the model with a holistic dataset and providing the most diverse cases. After careful data exploration, the WaDaBa plastic waste database was picked as the most eligible candidate for the model building process. The dataset consists of waste plastic images that are a good representation of any general plastic waste including industrial waste. In addition, the dataset has waste images in different angles, lighting conditions, and deformations. These factors make the dataset a great choice for training models to tackle real-world scenarios. The dataset consists of 4000 images taken for different plastic types. The entire dataset is 4GB in size. The images properties are as below:

- Format: JPG
- Pixels Size: 1920*1277
- Resolution: 300 dpi
- Palette: RBG 24 bits

The dataset comprises five categories of plastic that include PET(polyethylene terephthalate), PE-HD(high-density polyethylene), PP(polypropylene), PS(polystyrene), OO(Other). The images have been suitably named as per a naming convention that provides information on the plastic-type. A sample image for PET plastic is shown in Figure 4:

Figure 4: Sample Image - PET Plastic

The composition of the various plastic types can be seen in the below piechart.

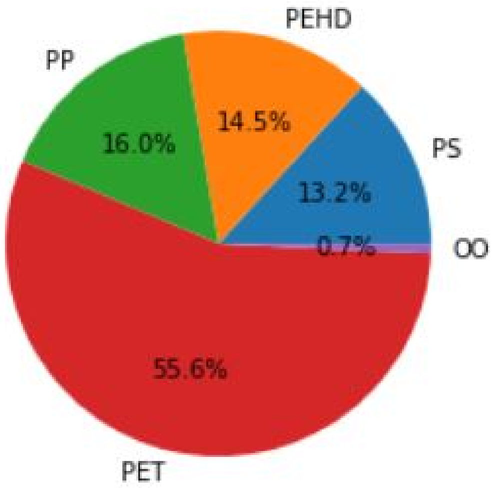


Figure 5: Plastic Data Composition

## 5.2 Data Preprocessing

The dataset comprises raw images which are unclassified. The dataset needs to be classified into different folders manually. The Roboflow app was used to work on the dataset to annotate the files and label them. The app provides customized export options to retrieve the data in a compressed format for ease of use. Uniform image files with manageable sizes are easy to handle and process. The images were resized to 416*416 and classified into folders based on their type. For classification problems, it is always better to have the images labelled and placed into folders as per their class. As we implement three models for our data classification, we have to consider the individual model requirements for data. The individual model requirements for the image size and specification will be handled in the individual model building phase.

## 5.3 Model Building

Three models were used to process the image dataset: Inception-ResNet-v2, VGG19, and Xception. The dataset was preprocessed to meet the requirements of each model, and the model was then trained. The features were transferred into a custom version of the model with different layers using transfer learning. To find the highest performing model, each model is independently tested and fine-tuned. The models were built in Python and ran on Google Colab, runtime engine was powered by Google Cloud VM.

### 5.3.1 Inception-ResNet-v2

The first model to be trained on the plastic trash dataset is the Inception-ResNet-v2 model. This model is the result of combining the inception architecture with residual connections. On top of the standard layers, batch normalization is constructed. This network can identify images from a wide range of categories. This has been possible due to availability of pre-trained weights by ImageNet, a database with lot of images from varied categories. A 299-by-299 image is fed into the network, and it outputs a list of estimated class probabilities. By freezing the output layer and training the model using ImageNet weights, transfer learning is conducted on the model. A customized output layer is then added later.

To feed the Inception-ResNet-v2 model, the dataset must be preprocessed. In the Roboflow software, the dataset has been divided into training and test sets and is ready to use. With the help of an image data generator, the photos in the training set are then enhanced by zooming, flipping, and rescaling them. With a batch size of 32, the photos are rescaled to 299 by 299 pixels.

The top classification layer is frozen after loading the Inception-ResNet-v2 model. The model is based on ImageNet weights that have been pre-trained. The base model's layer is frozen to prevent the weights from shifting during training. To develop a new model that is trained on the dataset, a classification head is added to the model. Five neurons are added to the custom output layer.

With a learning rate of 0.01 and momentum of 0.9, the model is built for categorical cross-entropy. With an epoch of 30, the model is trained on the training data. With a patience parameter of 20 epochs, an early stopper callback is created on the model to terminate the training if validation loss does not decrease. To save the model with less loss, a checkpoint callback is defined.

### 5.3.2 VGG19

The VGG19 model is based on the CNN architecture and is a version of the VGG model with 19 layers. 16 convolutional layers, 3 fully connected layers, 5 max pool layers, and 1 softmax layer are among the 19 layers. The VGG19 network may pass categorical classifiers as output and receives input in 224 by 224 format. Transfer learning aids in the construction of a new model based on the VGG19 architecture.

The image dataset is loaded with the help of python coding. The dataset is resized to 224 by 224 format for feeding to the VGG19 model. The image set is normalized to grayscale to reduce the illumination errors, it also helps the base CNN network to converge faster. The data is then split into train and test set in an 80:20 ratio.

The VGG19 model is initialized with ImageNet pretrained weights and the top layer is excluded in the model. All the layers in the model are frozen from getting altered during the training process. A new model is built by adding three new output layers to the VGG19 model. A max_pooling2d, flatten, dense layer with five neurons is added to the output of the model.

The model is compiled for categorical cross-entropy, with the optimizer set to adam. The model is then fitted on the training data with batch size set to 64, epoch set to 12. A call back is defined on the model to reduce the learning rate when the val_accuracy is reduced with patience set to 2.

### 5.3.3 Xception

The Xception model is a variation of the inception model, sometimes known as the extreme version of the inception model. The network has 71 layers and is densely packed with a diverse set of images. The deep learning model with depth-wise separable convolutions is what it's called. This means for n channels there are n by n spatial convolutions present.

The image dataset is loaded and a series is created with the image path and the class label for the image. The dataset is categorized into training and test set to make it ready for use. The training set images are augmented by zooming, flipping, resizing by an image data generator. The images are resized to 299 by 299 with a batch size of 32.

The Xception model is started without the top classification layer and with pre-trained weights from ImageNet. To prevent the model from changing throughout the training phase, all of the layers have been frozen. For our classifiers, we developed a new model with two dense layers and one classification layer with five neurons.

The model is compiled for categorical cross-entropy and the optimizer is set to adam. The model is trained for epoch set to 100 and a callback is defined for early stopping of the training in case of increase in val_loss with patience set to 2.

# 6 Model Results and Evaluation

The three models were implemented and finalized after training. The model finalization was done after an iterative process to find the most suitably fitting model after fine-tuning the parameters. The models were trained for different parameter settings to find the best training accuracy. A sampling approach was followed to categorize the data into training, validation, testing set. To achieve the research goals a comprehensive comparison was performed on the three models- Inception-ResNet-v2, VGG19, and Xception. The parameter settings have been kept different for each model to achieve maximum training accuracy for each model. The fine tuning of the model was done using the training data that pushed the accuracy further. The accuracy achieved for the three models has been tabulated in Table 2.

Table 2: Model Accuracy Comparison

| **Model** | **Learning Rate** | **Batch Size** | **Metric** | **Metric_Value** |
|---|---|---|---|---|
| Inception-ResNet-v2 | 0.01 | 32 | Accuracy | 95.86% |
| VGG19 | 0.001 | 64 | Accuracy | 98% |
| Xception | 0.01 | 32 | Accuracy | 92% |

## 6.1 Experiment 1 - Inception-ResNet-v2

The Inception-ResNet-v2 model after initialization and transfer learning was trained on the training data. The epoch for the model was set to 30 along with callback functions set to stop the training process on increase in loss during the training process. There was no undesired loss behaviour observed and the model was trained for the entire epoch of 30. The training accuracy achieved was 94.51% and after fine-tuning for 5 epochs the training accuracy was improved to 95.92%. The model's performance was examined on the test data and test accuracy achieved was 95.86%. The classification report for the model has been shown in Figure 6.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| OO | 0.89 | 1.00 | 0.94 | 17 |
| PEHD | 0.96 | 0.97 | 0.97 | 194 |
| PET | 0.96 | 1.00 | 0.98 | 621 |
| PP | 0.95 | 0.79 | 0.86 | 234 |
| PS | 0.82 | 0.91 | 0.86 | 134 |
| accuracy | | | 0.94 | 1200 |
| macro avg | 0.92 | 0.93 | 0.92 | 1200 |
| weighted avg | 0.94 | 0.94 | 0.94 | 1200 |

Figure 6: Inception-ResNet-v2 Classification Report

## 6.2 Experiment 2 - VGG19

The VGG19 model was trained and predictions were performed on the test data. The model was trained for epoch set to 12 and batch size of 64. The learning rate of the model was reduced twice in the training phase due to deterioration of the val_accuracy. The model ran for the entire epoch of 12 and the training accuracy delivered was 99.91%. The training accuracy achieved is impressive and the test accuracy delivered by the model is also good. The model test accuracy delivered is 98.12%. The classification report for the model has been shown in Figure 7.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| OO | 0.80 | 1.00 | 0.89 | 8 |
| PEHD | 0.99 | 1.00 | 1.00 | 120 |
| PET | 1.00 | 0.99 | 0.99 | 440 |
| PP | 0.97 | 0.95 | 0.96 | 128 |
| PS | 0.93 | 0.97 | 0.95 | 104 |
| accuracy | | | 0.98 | 800 |
| macro avg | 0.94 | 0.98 | 0.96 | 800 |
| weighted avg | 0.98 | 0.98 | 0.98 | 800 |

Figure 7: VGG19 Classification Report

## 6.3 Experiment 3 - Xception

With an epoch of 100 and a callback for an early halt on val loss increase, the Xception model is trained on the training data. The models' training was halted early at epoch 13 when the val loss value began to rise. The model attained a training accuracy of 100 percent. The model's accuracy in terms of training is good. The accuracy of the model was reduced to 91.75 percent when it was fitted to the test data. The model's classification report is depicted in Figure 8.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| OO | 1.00 | 0.62 | 0.77 | 8 |
| PEHD | 0.91 | 0.90 | 0.91 | 118 |
| PET | 0.96 | 0.98 | 0.97 | 447 |
| PP | 0.82 | 0.80 | 0.81 | 124 |
| PS | 0.82 | 0.84 | 0.83 | 103 |
| accuracy | | | 0.92 | 800 |
| macro avg | 0.90 | 0.83 | 0.86 | 800 |
| weighted avg | 0.92 | 0.92 | 0.92 | 800 |

Figure 8: Xception Classification Report

## 6.4 Error Analysis

There is a slight error observed in the predictions done by all three models. The error observed is due to the shortcomings of model training and limited fine-tuning performed. Another major factor is that the dataset for plastic waste is not well balanced which is understood as some of the types of plastic are very rarely used and for specific purposes. Also, some of the plastic objects from different plastic types are similar in resemblance. This factor also drives incorrect predictions. One such example can be seen in Figure 9.

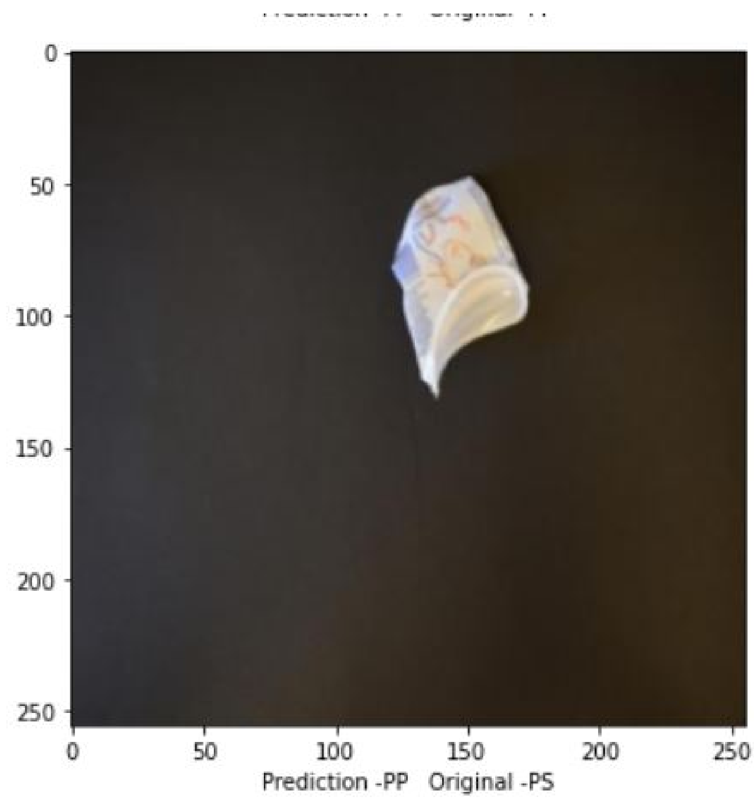


Figure 9: Incorrect Prediction Sample

## 6.5 Discussion and Model Comparison

All three models under consideration have been satisfactorily trained and tested. The WaDaBa dataset was sufficient enough to derive meaningful results from the models. Detailed analysis and comparison of the models are required to conclude with the best model and architecture. The research work performed was on the classification problem. The following figure is a comparison of the models under scrutiny based on their accuracy and run times. Run time is also a key indicator that is often ignored as it matters a lot when it comes to delivering efficient models that are quick and reliable. The model with the highest training accuracy was the Xception model. But, when it comes to the test accuracy, VGG19 delivers the highest accuracy of 98.12%. The computational time for VGG19 also was decent. Taking into consideration all these factors we can say that VGG19 is the best performing model. A visual comparison of the models' performance is shown in Figure 10.

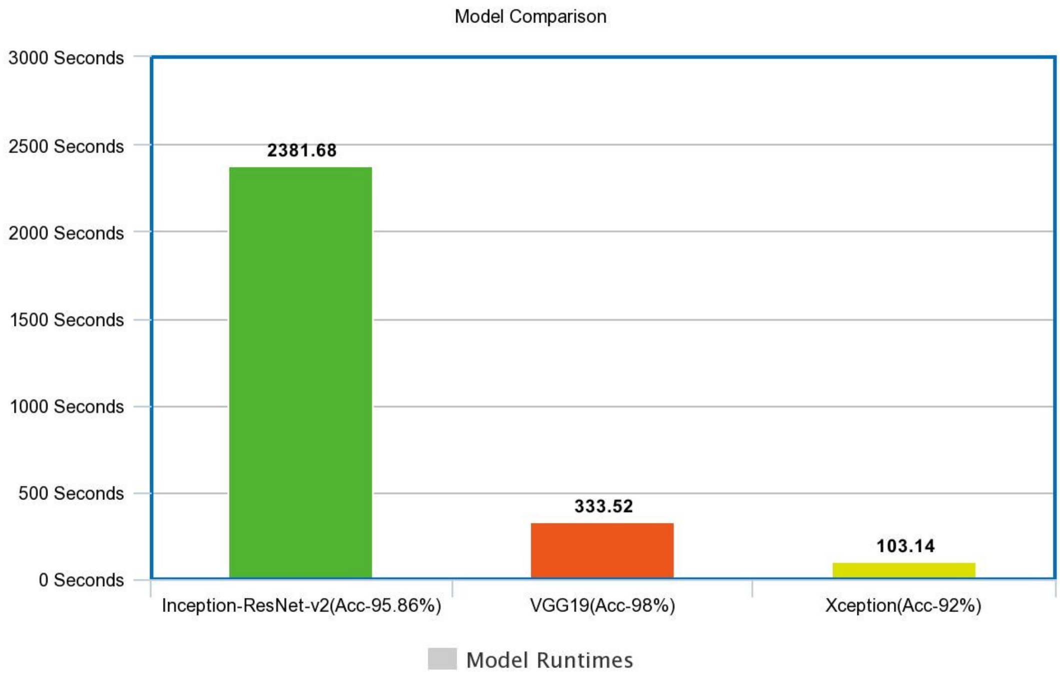


Figure 10: Model Stats Comparison

VGG19 outperforms the other models with the help of its 19 deep connected layers that enables it to perform better than other deep learning models in general. It was evident from the results as better accuracy and performance was delivered by VGG19.

# 7 Conclusion and Future Work

The research paper has thoroughly discussed the deep learning models and their image classification capabilities. The WaDaBa dataset acquired has a collection of realistic plastic samples that helps the research work with a very enriched data source. The deep learning models capabilities in classifying waste images was efficiently demonstrated. The approach and model implementation done throughout the research was motivated by previous research work conducted in a similar field related to waste management and image classification. The plastic dataset was used to train and test the three models: Inception-ResNet-v2, VGG19, and Xception. The accuracy and computing time of each model's findings were compared, and VGG19 was determined to be the best performer.

The research work carried out opens up a plethora of possibilities ahead in terms of new model building and application of the model. The performance seen by the models is impressive, and it will be interesting to see how the dataset will deliver with the latest state-of-the-art pretrained models like YOLOR. Initial trials were performed for the dataset on YOLOv5 but due to time constraint more study could not be done. The same models can be used to fit on a plastic dataset that covers more plastic types which is more balanced overall. The model implemented can be pushed ahead and integrated with cameras, hand-held devices to have a real-time system that can keep on learning and provide a real-time classification of the plastic waste.

The model developed is quite robust and can be very helpful in the classification of plastic waste in urban or industrial waste. The model will help segregate plastic into different types that will help in easing the recycling process of plastics. Plastics of different types have different recycling needs. This system will also help in keeping a check on industrial waste with high levels of non-recyclable plastics.

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